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FORMULATING AN EXPANDED UTAUT2 MODEL TO INVESTIGATE DETERMINANTS IMPACT ON CONSUMER ADOPTION OF ARTIFICIAL INTELLIGENCE

Muhammad Saad Ullah*[1], Muhammad Ahmad Siddiqui[2], Junaid Ahmed[3], Muhammad Naeem[4], Sami ul Haq[5]

*[*1]MS Management Sciences, University Institute of Management Sciences, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan*
[2]Department of Computer Science, University of the Punjab, Lahore
[3]PhD scholar, Business School of Qingdao University China
[4]Assistant Professor, Foundation University Islamabad
[5]MS Management Sciences, University Institute of Management Sciences, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan

[*1]Msaadiqbal99@gmail.com; [2]asahmadsiddiqui@gmail.com; [3]asolangi670@gmail.com, [4]m.naeem@fui.edu.pk, [5]Samikakar007@gmail.com

Corresponding Author: *

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ABSTRACT
This research aims to enhance the adoption of AI in Pakistan to increase their work performance. The researcher expands the UTAUT2 model with perceived trust in this current research. In methodology, the researcher used a non-probability sampling method for data collection, and the unit of analysis was the user of Artificial Intelligence devices. This research used a survey method and data were collected through the online Google form. The sample size was 357, for data analysis two software were used first one is SPSS and Smart-Pls, structural equational model (SEM). SEM is used for measurement and structural modeling. The measurement model was used for validity and reliability, and the structural model was used for testing the hypotheses. The finding of this research is that all factors like performance expectancy, effort expectancy, facilitating condition, hedonic motivation, perceived trust, and behavioral intention play a major role in adopting artificial intelligence. The originality of this research conducted in Pakistan expands the utaut2 model with perceived trust. The primary objective is to gain valuable insight into organizations, specifically consumer adoption of AI. This study is conducted on the comprehension of consumer behavior to spare the adoption of AI.

Keywords: Performance expectancy, effort expectancy, Hedonic motivation, Adoption, Artificial intelligence, perceived trust.

1.INTRODUCTION

In this current era, many consumers connect with advanced technology, which has helped consumers' way of life shift from one activity to another (Zogaj et al., 2023). Consumers have shifted from a brick-and-mortar approach to a Digital platform (Zogajet al., 2023). The advancement of digital platforms has improved human activities including artificial intelligence (AI) and a strategy rooted in enabling the success of a consumer (Das et al., 2024). Before the digital platform customers physically visit the shop to get product-related information. Digital platforms always help the consumer to search for a proactive product, when consumers are determined to purchase a product through a digital tool (Bawack et al., 2021).

Consumer adoption of artificial intelligence enhances consumer performance by offering personalized recommendations and streamlining the shopping experience through predictive analytics and targeted marketing strategies (Mariani et al., 2023). This information allows and helps individuals to buy products with the use of AI (Mariani et al., 2023). Consumers always explore product-related information immediately as they want. Sometimes Consumers do not get product-related guidance, they become unsatisfied with purchasing the product and always move to the other competitor's products for a long time (Troshani et al., 2021). Many consumers feel hesitant when they adopt AI (Ho & Chow., 2023).

According to the study of Boston, 2023, Over half of the consumers (53%) prefer or choose to the real humans when it comes to complex situations or customer services issues. Only (17%) would choose to opt the technology like live chat via website (Boston, 2023). When dealing with AI for customer service questions or problems nearly half (46%) of customers surveyed also prefer to speak to a human but they feel happy when the human-like agent is using AI to improve the interaction (Boston, 2023). The survey result shows that consumers are less interested in the use of AI.

The main problem 83% of customers are satisfied with real humans instead of using AI when they want to review a product or purchase products, that results in a waste of resources and deterioration of performance. There is a need to study the factors contributing to consumers' adoption of AI. Furthermore, behavioral intention mediates in this current research and consumer adoption of AI.

In previous research in the area of consumer purchase intention, many of the researchers used the Theory of Reasoned Action (TRA) or the Theory of Planned Behaviour (TPB) (Rozenkowska, 2023). Numerous studies examine the impact of the UTAUT2 model on the adoption of digital payment systems (Al-Okaily, 2023). Some of the other studies also used the UTAUT2 model in healthcare centers (Cobelli, 2024). After studying of large amount of articles the researcher cannot find the research on the UTAUT2 model in Consumers' adoption of AI. Many consumers believe humans are much better than AI at the stage of complex situations at answering several questions (Chakraborty et al., 2024). A recent research found that customers feel unsatisfied when they use AI, they think AI is less knowledgeable than real humans; thus the result found that they make a less purchases (Mariani et al., 2023).

Despite the number of studies in this area, there are substantial and important gaps in the literature. In this study to fill the research gap, an extension of the UTAUT2 model is undertaken, Additionally, some other variables add to the UTAUT2 model. The comprehensive investigation aims to discern the impact of these augmented variables, along with the existing UTAUT2 factors, on consumers' adoption of artificial intelligence.

2. Literature Review

2.1 Adoption of AI

Consumer adoption of AI in marketing is influenced by consumer behavior (Vidhya et al.,2023). Positive perceptions of AI's capabilities in enhancing personalized experiences, improving recommendations, and streamlining decision-making processes can lead to higher purchase intentions (Malhotra & Ramalingam, 2023). Effective communication about AI's advantages and addressing potential concerns can further boost consumer performance expectancy, effort expectancy, facilitating condition, and hedonic motivation and foster increased adoption of AI-powered marketing (Haenlein et al., 2019). With the use of artificial intelligence consumer can explore the category of products. AI is a very powerful to engage customers directly (Araujo, 2018). AI has a different name in literature like bot agent, e-service agent, virtual agent and intelligence agent (Ciechanowski et al., 2019, Edwards et al., 2014, Chung et al., 2018). AI also helps to the individuals.

2.1 Theory

UTAUT2 was developed by (Venkatesh et al., 2012) by reviewing nine models or theories on technology acceptance and human behavior. UTAUT2 is the contemporary theory to examine consumer BI. This was realized by discussing the theories and practices underpinning research on the psychology of human behavior, as well as motivation, and adopting the new technology.

2.3 Performance Expectancy

Performance expectancy is a crucial construct of the UTAUT2 variable that indicates that individuals accept technology to improve job Performance (Venkatesh et al., 2003). PE refers to the perceived effectiveness or usefulness of a particular technology or system in achieving desired outcomes (Kosasi et al., 2023). Previous research shows that performance expectancy has a positive effect on adoption of mobile banking (Purohit et al., 2022). If it is increasing their performance they are more likely to adopt AI (Pham et al., 2024). When AI solutions align with an individual’s personal or professional objectives, the perception of performance expectancy strengthens. For instance, an employee might adopt AI tools that can assist with data analysis or decision-making, increasing performance and job satisfaction (Tanantong & Wongras, 2024). Based on the preceding information, this study proposes hypotheses suggesting that the PE required significantly positive impacts on consumers' behavioral intentions. Hence based on the previous study, the following hypotheses are proposed.

H1: Performance Expectancy has a positive and significant impact on consumer's behavioral intention.

2.4 Effort Expectancy

Effort expectancy is a construct of the UTAU2 variable. Effort expectancy is the belief that using technology to make work easier can be learned quickly (Venkatesh et al., 2012). Effort expectancy is a term commonly used in the field of technology acceptance and usability studies (Lin, 2022). Individuals show a high interest in the adoption of technology when they know how to make work easier with the help of technology (Faqih & Jaradat, 2021). Effort Expectancy is the degree to which a person believes that using a technology will be free of effort. The more effortless a technology is perceived to be, the more likely individuals are to adopt and use it. Previous research shows that Effort expectancy has a positive effect on online shopping (Ryu and Fortenberry., 2021) adoption of Internet banking (Rahi et al., 2019). Effort expectancy helps individuals to make work easier effectively and efficiently. Hence based on the previous research, the following hypotheses are proposed.

H2: Effort Expectancy has a positive and significant impact on consumer's behavioral intention.

2.5 Facilitating Condition

The Person believes that the necessary administrative and technical infrastructure is in place to make the system usable (Venkatesh et al., 2003). FC refers to the perceived availability of resources and support rather than being a facilitating condition itself (Lutfi, 2022). This includes technical support, access to necessary hardware and software, training, and organizational policies and procedures that endorse the utilization of the technology. Users have access to the necessary hardware and software infrastructure, they are more likely to have a positive behavioral intention to adopt AI. For example, having reliable internet access, powerful computing systems, and AI tools that are easy to integrate into existing workflows can enhance users' motivation to adopt AI technologies (Pillaiet al., 2022). Previous study shows that facilitating conditions have a positive and significant on online education (Buraimoh et al., 2023). Facilitating conditions helps reduce barriers to adoption, ensuring that users feel confident and capable in their ability to engage with the technology. Hence, based on prior exploration, the following hypotheses are assumed.

H3: Facilitating conditions has a positive and significant impact on consumer's behavioral intention.

2.6 Hedonic Motivation

HM is a type of motivation driven by the use of technology. It is based on the assumption that consumers are motivated to seek out positive experiences and emotions while avoiding negative ones (Lin et al., 2022). This idea of Perceived pleasure is believed to impact customer acceptability and the use of technology. This may involve designing user interfaces that are visually appealing and easy to use, incorporating elements of gamification or other enjoyable activities, and highlighting the potential social benefits of using the technology (Yuniarta & Purnamawati, 2021). Previous research shows that hedonic motivation has a positive and significant effect on electronic payment like mobile banking, digital banking, and e-wallet (Khatimah et al., 2019). Users who find AI-driven applications enjoyable, entertaining, or intellectually stimulating are more likely to adopt these technologies, as their usage is perceived as intrinsically rewarding. Considering the above conflicting opinions, these hypotheses are proposed.

H4: Hedonic motivation has a positive and significant impact on consumer's behavioral intention.

2.7 Perceived Trust

Trust is widely recognized as a key factor in the adoption of new technologies (Söllner et al., 2016). Consequently, numerous studies have explored the relationship between trust and the Technology Acceptance Model (TAM). For example, trust has been examined in the context of new information systems (Tung et al., 2008) and various online services, including online games (J. Wu & Liu, 2007), online banking (Suh & Han, 2002), social networking sites (Sledgianowski & Kulviwat, 2009), and online shopping (Gefen et al., 2003).

Recent research continues to highlight the importance of trust in TAM. For instance, Shin (2021) found that trust positively influences the continuous use of a news recommendation system, while Shin (2021) demonstrated that trust in AI predicts both perceived usefulness and ease of use. Similarly, Beldad and Hegner (2018) showed that trust does not directly impact the intention to use a health tracking app but instead shapes users' perceptions of its usefulness. Other studies align with these findings, indicating that trust indirectly influences usage intention by enhancing perceived usefulness and fostering positive attitudes.

H5: Perceived Trust has a positive and significant effect on the adoption of AI.

2.8 Behavioral Intention

BI refers to an individual's conscious decision or plans to perform a particular behavior in the future. It is a critical social psychology and behavioral sciences concept that helps explain and predict human behavior. BI is a Person's propensity to embrace new technology (Mohd et al., 2012). According to Raza et al., (2019), the intention to utilize technology changes and is strongly dependent on the technology's characteristics. BI is a key construct that they will decide to accept or reject anything (Ifedayo et al., 2021).Previous research shows that behavioral intention has a positive and significant effect on technology adoption (Park et al., 2012).When individuals exhibit a strong intention to use AI, they are more likely to overcome initial skepticism and engage with AI-driven solutions, perceiving them as beneficial and aligned with their needs. Hence on the base of previous research, this study proposed the following hypotheses.

H6: Behavioral intention has a positive and significant effect on the Adoption of AI.

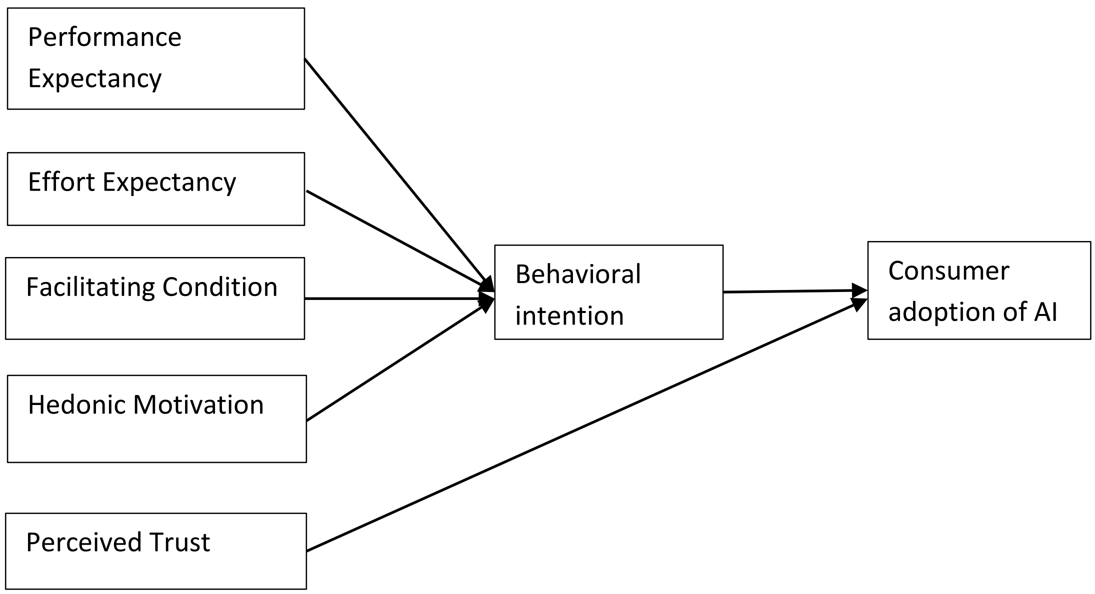

Figure 2.1: Theoretical framework

3. Research Methodology

3.1 Instrument of Measurement

This research utilized an online Google Form to collect data, with measurement scales for the constructs adopted from prior studies (Venkatesh et al., 2012; Oliveira et al., 2016). The study aimed to investigate various factors influencing behavioral intention (BI) and the adoption of artificial intelligence (AI). All measurement instruments were adapted from previous research. Constructs such as performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), perceived trust (PT), Behavioral intention, and adoption of AI. The survey method, commonly employed by researchers (e.g., Kim and Bae, 2023), included close-ended questions based on a five-point Likert scale, where 1 indicated "strongly disagree" and 5 indicated "strongly agree."

3.2 Sampling and Data Collection

This study employed a non-probability purposive sampling method to collect primary data through a survey. Purposive sampling enables researchers to use their discretion and judgment to select participants who meet specific criteria (Henry, 1990; Limna et al., 2021). Data were collected from participants in Islamabad and Rawalpindi, Pakistan, focusing on individuals who use AI-based technologies. The sample size comprised 357 respondents.

3.3 Data Analysis Tool

Data analysis was conducted using both SPSS and SmartPLS. SPSS was utilized for demographic analysis, while SmartPLS 4 was employed for structural equation modeling (SEM), which allows for simultaneous exploration of multiple relationships. PLS-SEM is particularly suitable when limited sample sizes (Ghaffar et al., 2023).

3.4 Demographics Profile

Table 3.1 Demographics Profile

Profile	Distribution	Frequency	Percentage
Age	18-29	172	48.1%
	30-39	113	31.6%
	40-49	49	13.7%
	50 or Above	23	6.4%
	Total	357	
Gender	Female	148	41.4%
	Male	209	58.5%
	Total	357	
Marital Status	Married	114	31.9%
	Single	243	68.0%
	Total	357	
Education	Matriculation	41	11.4%
	Intermediate	97	27.1%
	Under Graduate	126	35.2%
	Post Graduate	93	26.05%
	Total	357	
Income level	50,000 and below	117	32.7%
	51,000-100,000	148	41.4%
	101,000-150,000	68	19.0%
	151,000 or Above	26	7.2%
	Total	357	
Population	Islamabad	113	31.6%
	Rawalpindi	244	68.3%
	Total	357	

4. Result

4.1 Measurement model (Reliability and Validity)

The table presents the results of a reliability and validity analysis for constructs related to user adoption of AI. Each construct is evaluated using multiple indicators, with their respective factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Adoption of AI, the factor loadings for its four indicators range from 0.753 to 0.857, with strong internal consistency indicated by a Cronbach’s alpha of 0.822, CR of 0.824, and AVE of 0.650. Behavioral Intention also demonstrates strong reliability, with factor loadings between 0.775 and 0.897, a Cronbach’s alpha of 0.875, CR of 0.874, and AVE of 0.730.

Effort Expectancy has four indicators with factor loadings from 0.741 to 0.806, yielding a Cronbach’s alpha of 0.793, CR of 0.796, and AVE of 0.617. Similarly, Facilitating Condition includes four indicators, with factor loadings between 0.782 and 0.825, and reliability metrics of Cronbach’s alpha at 0.829, CR at 0.829, and AVE at 0.661. Hedonic Motivation has three indicators with strong factor loadings (0.851 to 0.866) and reliability scores of Cronbach’s alpha at 0.819, CR at 0.820, and AVE at 0.734. Performance Expectancy reliability, with factor loadings ranging from 0.653 to 0.858, a

International Journal of Social Sciences Bulletin
Volume 2, Issue 4, 2024 ISSN: (E) 3007-1917 (P) 3007-1909

Cronbach's alpha of 0.734, CR of 0.760, and AVE of 0.560. And Perceived Trust includes three indicators with factor loadings from 0.790 to 0.838, achieving a Cronbach's alpha of 0.735, CR of 0.735, and AVE of 0.651.

According to Hair et al. (2014), these results indicate that most constructs exhibit satisfactory reliability and convergent validity, as evidenced by Cronbach's alpha values above 0.7 and AVE values exceeding 0.5. All of the value show in Table 4.1.

Table 4.1: Measurement model (Reliability and Validity)

Constructs	Indicators	Factor Loading	Cronbach's alpha	CR	AVE
Adoption	Adoption1	0.754	0.822	0.824	0.650
	Adoption2	0.753			
	Adoption3	0.854			
	Adoption4	0.857			
Behavioral Intention	BI1	0.775	0.875	0.874	0.730
	BI2	0.842			
	BI3	0.896			
	BI4	0.897			
Effort Expectancy	EE1	0.791	0.793	0.796	0.617
	EE2	0.806			
	EE3	0.802			
	EE4	0.741			
Facilitating Condition	FC1.	0.822	0.829	0.829	0.661
	FC2	0.821			
	FC3	0.825			
	FC4	0.782			
Hedonic Motivation	HM1	0.866	0.819	0.820	0.734
	HM2	0.851			
	HM3	0.853			
Performance Expectancy	PE1.	0.689	0.734	0.760	0.560
	PE2	0.858			

Constructs	Indicators	Factor Loading	Cronbach's alpha	CR	AVE
	PE3	0.776			
	PE4	0.653			
Perceived Trust	PT1	0.838	0.735	0.735	0.651
	PT2	0.790			
	PT3	0.793			

4.2 Discriminant Validity
4.2.1 Heterotrait-Monotrait (HTMT) ratio

Discriminant validity assesses whether constructs that are supposed to be distinct are indeed empirically distinct, often evaluated using the Heterotrait-Monotrait (HTMT) ratio of correlations. The HTMT matrix provides pairwise ratios of heterotrait-heteromethod correlations relative to monotrait-heteromethod correlations, where values below the threshold (commonly 0.85 or 0.90) indicate adequate discriminant validity. In the presented HTMT matrix, the values between constructs such as Adoption, Behavioral Intention (BI), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Performance Expectancy (PE), and Perceived Trust (PT) are all below the typical thresholds, suggesting that discriminant validity is established among these constructs. For instance, the HTMT value between Adoption and BI is 0.591, while the highest observed value is 0.766 (between EE and FC), both well within acceptable limits. All of the Values show in Table 4.2.

Table 4.2: Heterotrait-Monotrait ratio (HTMT)

	Adoption	BI	EE	FC	HM	PE	PT
Adoption							
BI	**0.591**						
EE	0.653	**0.667**					
FC	0.634	0.631	**0.766**				
HM	0.539	0.542	0.568	**0.629**			
PE	0.230	0.364	0.214	0.275	**0.273**		
PT	0.599	0.641	0.710	0.677	0.580	**0.358**	

Table 4.3 presents the R-Square and Adjusted R-Square values for two dependent variables: Adoption and Behavioral Intention. For Adoption, the R-Square is 0.327, indicating that the independent variables explain 32.7% of the variance in Adoption, with an Adjusted R-Square of 0.323, slightly lower due to adjustments for the number of predictors. For Behavioral Intention, the R-Square is higher at 0.421, showing that 42.1% of its variance is accounted for by the predictors, with an Adjusted R-Square of 0.415, similarly reflecting minor adjustment for model complexity. This suggests that the predictors have a stronger explanatory power for Behavioral Intention compared to Adoption.

International Journal of Social Sciences Bulletin
Volume 2, Issue 4, 2024 ISSN: (E) 3007-1917 (P) 3007-1909

Table 4.3 R- Square and Adjusted R-Square

	R-Square	R-Square Adjusted
Adoption	0.327	0.323
Behavioral intention	0.421	0.415

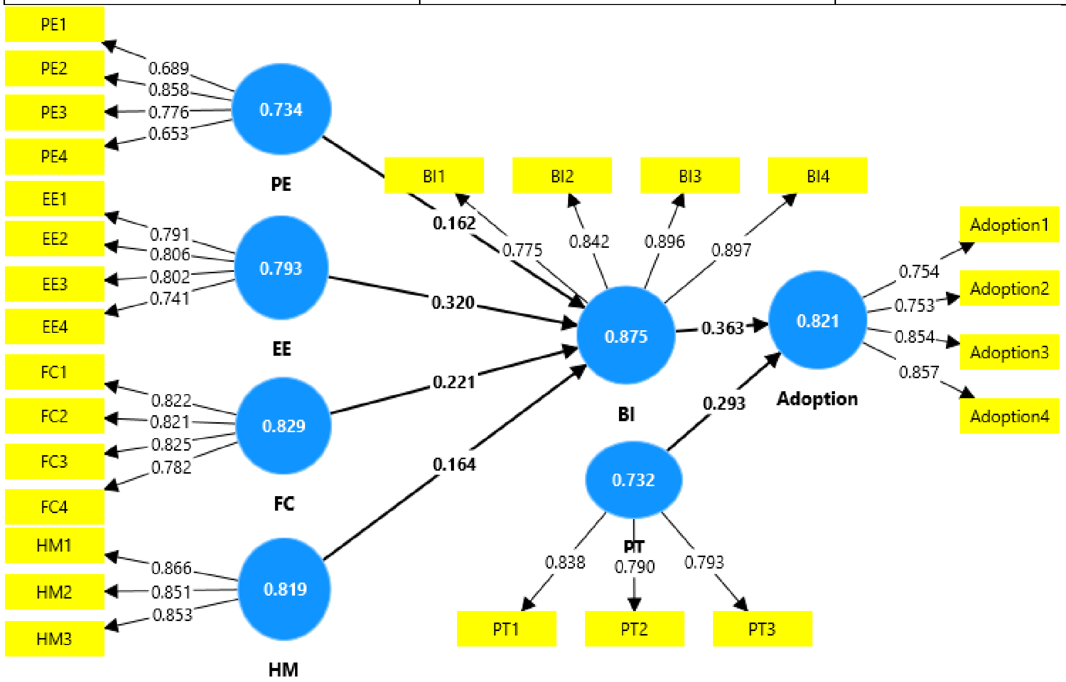

Figure 4.1: Measurement model

4.4 Path Coefficient

The table 4.4 presents the results of a structural equation model, showing the relationships between various predictors and their outcomes. Behavioral Intention (BI) significantly influences Adoption (path coefficient = 0.363, $p < 0.001$). Among the predictors of BI, Effort Expectancy (EE) has the strongest effect (0.320, $p < 0.001$), followed by Facilitating Conditions (FC) (0.221, $p = 0.002$), Hedonic Motivation (HM) (0.164, $p=0.007$), and Performance Expectancy (PE) (0.162, $p=0.001$). Perceived Trust (PT) directly impacts Adoption significantly (0.293, $p<0.001$). All relationships are statistically significant, as indicated by high T-statistics and pp-values below 0.05.

Table 4.4 Path Coefficient

	Original sample (O)	Sample mean (M)	(STDEV)	T statistics	P values
BI -> Adoption	0.363	0.362	0.068	5.320	0.000
EE -> BI	0.320	0.319	0.068	4.685	0.000
FC -> BI	0.221	0.222	0.070	3.165	0.002
HM -> BI	0.164	0.165	0.060	2.714	0.007
PE -> BI	0.162	0.168	0.049	3.318	0.001
PT -> Adoption	0.293	0.298	0.065	4.541	0.000

Discussion

The current research expands the UTAUT2 model, the additional variable is perceived trust. Existing study findings reveal that performance expectancy has a positive and significant effect on behavioral intention in the adoption of artificial intelligence. The previous study results show that performance expectancy has a positive and significant effect on the adoption of new technology like mobile banking (Purohit et al., 2022). Likewise, this current research shows that effort expectancy has a positive and behavioral intention to the adoption of artificial intelligence. Although, previous research supports our current research, according to Ryu and Fortenberry., (2021) Effort expectancy has a positive effect on behavioral intention to the adoption of online shopping. In this current research facilitating conditions have a positive and significant effect on behavioral intention to the adoption of artificial intelligence. Moreover, the previous study shows that facilitating conditions has a positive and significant effect on online education (Buraimoh et al., 2023). Hedonic motivation has a positive and significant effect on behavioral intention to the adoption of artificial intelligence, and the previous research supports our current research hedonic motivation has a positive and significant effect on electronic payment like mobile banking, digital banking, and e-wallet (Khatimah et al., 2019). Also, discuss the additional variable of perceived trust that has a positive and significant effect on the adoption of artificial intelligence. past study shows that perceived trust has a positive and significant effect on the adoption of artificial intelligence. In last this current research has a direct positive and significant effect on the adoption of artificial intelligence. previous research also supports our research like technology adoption (Park et al., 2012).

Implications

Theoretical Implication

Theoretical implications of formulating an expanded UTAUT2 model incorporating "perceived trust" to investigate consumer adoption of Artificial Intelligence (AI) lie in enhancing our understanding of user behavior in technologically dynamic contexts. By integrating perceived trust, which encompasses users' confidence in the reliability, transparency, and ethical use of AI, the model addresses critical gaps in explaining adoption behaviors specific to AI systems. Trust is increasingly recognized as a pivotal factor in contexts where autonomous decision-making and data privacy concerns dominate consumer perceptions. Its inclusion in the UTAUT2 framework enriches the explanatory power by bridging technical functionalities with psychological and social dimensions of user experience. This expanded model not only refines theoretical predictions but also provides actionable insights for developers and policymakers to design AI systems that align with consumer expectations, ultimately fostering widespread adoption and sustainable innovation.

Practical Implication

The practical implications of formulating an expanded UTAUT2 model with the inclusion of perceived trust as an additional variable highlight its potential to provide deeper insights into consumer adoption of artificial intelligence (AI). By integrating perceived trust, organizations and developers can better understand how trust influences user acceptance, beyond traditional factors like performance expectancy, effort expectancy, and social influence. This enhanced model allows for identifying critical trust-building strategies, such as ensuring transparency, security, and ethical AI practices, which can address user concerns and improve adoption rates. Consequently, the expanded UTAUT2 model serves as a robust framework for guiding AI product design, marketing strategies, and policy development, fostering broader acceptance and responsible use of AI technologies.

Limitations and Future Research

This study employs a non-probability sampling method, which may limit the generalizability of the findings to the broader population. Additionally, relying on self-reported data collected through an online survey (Google Forms) could introduce response bias, as participants might provide socially desirable answers. The study is context-specific to Pakistan, which could restrict the applicability of the results to other cultural or regional settings. Finally, while the inclusion of perceived trust expands the UTAUT2 model, other potentially relevant factors influencing AI adoption, such as organizational culture or regulatory frameworks, were not considered.

Future research should explore additional variables influencing AI adoption in Pakistan, such as cultural dimensions, regulatory frameworks, and organizational readiness, to provide a more comprehensive understanding of the factors driving AI integration. Expanding the scope beyond individual users to include organizational perspectives could yield insights into broader adoption trends. Longitudinal studies could also examine the evolution of AI adoption over time and its impact on productivity and innovation. Furthermore, comparative studies between Pakistan and other countries with similar socio-economic conditions could identify best practices and challenges unique to specific contexts. Advanced methodologies, such as mixed methods or experiments, could be employed to deepen the understanding of causal relationships and refine the extended UTAUT2 model.

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